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Forecasting Utilization of Toll-Free Numbers

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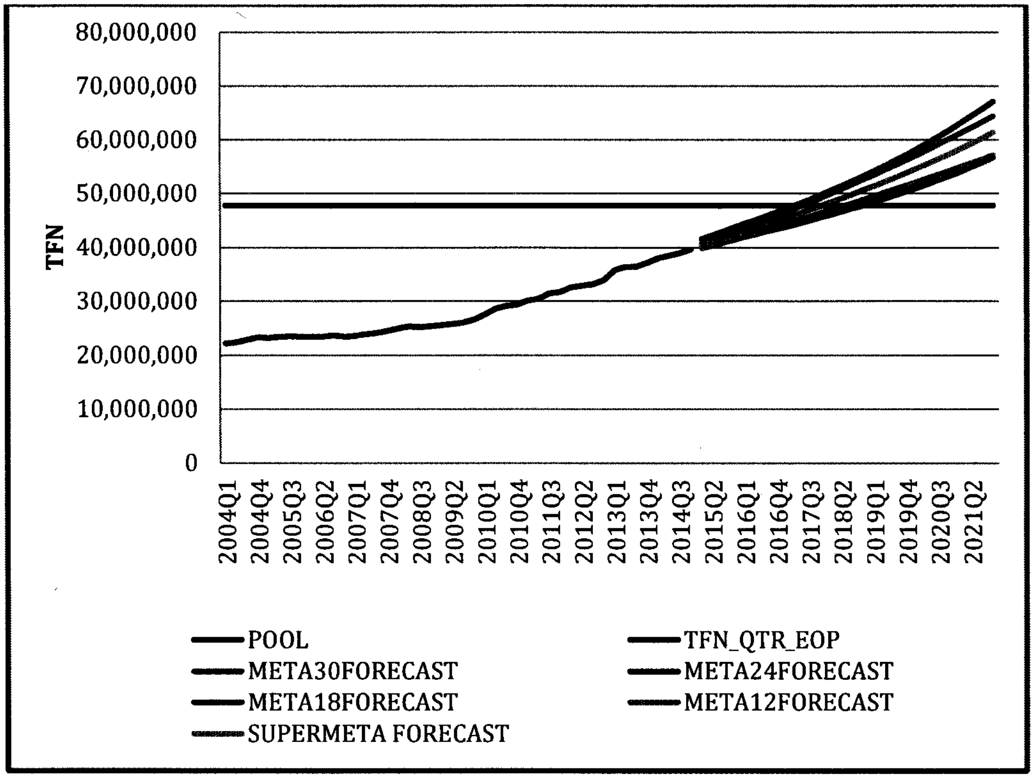
Executive Summary

The business decision facing SMS/800, Inc., its industry associates and regulators is when to start the planning and development effort required to open a new toll-free Numbering Plan Area (NPA). Pursuant to ATIS guidelines[1], that planning begins with an announcement to the industry when the forecasted exhaust date for the existing toll-free number (TFN) pool is within 30 months. Historically, the responsible stewards of TFN resources have applied a more conservative approach, recommending announcement of new NPAs earlier than required by the guidelines. A preponderance of caution might lead to opening codes even earlier – or perhaps to open several codes at once. However, such a practice would require the industry to commit resources far earlier than actually needed, so the objective is to seek an appropriate balance in the timing the announcement. The balance sought is to allow the toll-free industry an appropriate amount of time to plan for a new code opening while avoiding any substantive risk that the TFN pool might exhaust prior to the intended opening.

Compliance with the announcement deadline requires that SMS/800 anticipate the industry's usage of TFNs more than 30 months in the future. To inform this process, SMS/800 employs statistical forecasting. A variety of candidate statistical models are considered using an approach comparable to that employed in previous studies, examining data from 1997 through 2014[2].



As seen in the graph above, the current analysis produced several models that performed reasonably well for certain sample tests and data characteristics. Exhaust dates for these models (Meta12, Meta18, Meta24 and Meta30) vary from the second quarter 2017 through the fourth quarter 2018 – six quarters difference depending on the underlying data characteristics and model specification. No models or meta-models performed well for all

[1] "Toll Free Resource Exhaust Relief Planning Guidelines" (ATIS-0300057), published July 1998.

[2] The statistical techniques used to develop these projections rely on historical data and, thus, cannot predict turning points or dramatic changes in TFN growth that are not reflected in the historical data. Thus, the forecasting exercise that SMS/800 has performed simply describes the most likely date that toll-free number capacity will be reached if the data patterns of August 1997 through December 2014 should continue into the future.

sample tests, and thus these four meta models were combined into a supermeta model. The supermeta model predicts exhaust in the first quarter of 2018.

Although forecasting an exhaust date is essential in determining when SMS/800, Inc. and the industry should announce a new code, it does not adequately convey the degree of risk and uncertainty (whether large or small) inherent in any forecast. Meteorologists, for example, present rain forecasts as "the chance of rain" on a particular date. Their audience weighs the probability of rain to decide whether to carry an umbrella. In a forecast of future TFN growth, forecast risk occurs because historical data demonstrate that the growth in TFNs is variable. At times, usage can accelerate quickly, as occurred during the late 2009 to early 2010 period and during March 2013; at other times usage can decelerate or even decline as occurred in 2000-2003. While the TFN forecast provides the most likely exhaust date, the forecast risk warns that history has demonstrated that earlier exhaust is clearly possible. Thus, based on the supermeta forecast, SMS/800's methodology also assesses the risk of exhaust at particular dates in the near future.

Date	Spare % of TFN Pool	% of TFN Pool in Use	Probability of Exhaust
2015Q2	15%	85%	Less than 1%
2016Q1	10%	90%	Less than 1%
2017Q1	5%	95%	Less than 3%
2017Q2	3.1%	96.9%	10%
2017Q3	1.7%	98.3%	26%
2017Q4	0.2%	99.8%	47%
2018Q1	0%	100%	66%

In early February 2015, with more than 8 million TFNs in the spare pool, the probability of exhausting TFNs prior to the end of the second quarter 2015 is miniscule, much less than 1%. The probability remains small even as the quantity of TFNs forecast to remain in the spare pool falls to 4.77 million (10% spares) during the first quarter of 2016. In the year that follows, the remaining spare pool depletes by half to 5%, yet the probability of exhaust remains low, less than 3%. However, in the quarter that follows (the second quarter of 2017), an additional 1.9% of the spare pool is in use while the probability of exhaust more than triples, jumping to 10%. Another quarter passes and the probability of exhaust jumps again, more than doubling to 26%. Probability of exhaust nearly doubles again during the last quarter of 2017, as the expected spare pool depletes further and finally exhausts during the first quarter of 2018.

Again, the first quarter 2018 is only the most likely exhaust date based on the statistical analyses, i.e., there is a 50% chance of exhaust in that quarter. The table above, however, demonstrates how rapidly the risk of exhaust escalates in the year prior to the point forecast date. In the year between the first quarter 2017 and the first quarter 2018, the probability of exhaust accelerates dramatically.

The results of the statistical analyses identify a date of likely exhaust, *but also demonstrate a substantive risk of earlier exhaust*. Given the significance of early exhaust of the TFN pool and the impact that any rationing of TFNs might have on the toll-free industry, the following recommendations are offered for the industry's consideration.

1. Open code 833 at the end of first quarter, 2017. Although this date is prior to the currently forecasted TFN exhaust in first quarter of 2018, less than 5% of the pool (2.38 million) is forecast to remain at the end of first quarter, 2017. Furthermore, probabilistically, the risk of exhaust starts to escalate very rapidly during the second half of 2017. Conservative practice suggests an earlier opening to mitigate the risk of exhaust. If by April, 2015 SMS/800 were to recommend a code opening date of April 1, 2017, the industry would have two years to prepare for the new code, and the announcement would be more than 30 months prior to the forecast exhaust of first quarter, 2018.

2. Continue to monitor TFN growth carefully to see if growth accelerates toward its long-term historical path. Although recent growth in TFNs has been more moderate, long-term patterns of TFN change reflect faster, accelerating growth. A resumption of such accelerating growth would exhaust the existing pool of TFNs more quickly, possibly even earlier than spring, 2017.

3. Develop and be prepared to implement contingency plans to address the possibility of early exhaust. Even if code 833 were opened April 1, 2017, resumption of accelerating growth could exhaust the existing pool of TFNs even earlier. It is prudent to prepare a contingency plan to address this possibility.

1 Introduction

The toll-free industry has a limited supply of toll-free numbers (TFNs). There are currently six open Numbering Plan Areas (NPAs): 800, 888, 877, 866, 855 and 844, resulting in a total of 47,770,094 TFNs available[3]. By December 27, 2014, TFNs in Use had reached 39.65 million—about 83% of the 47.77 million TFNs available for use. Thus, about 8.12 million TFNs remained in the spare pool, the equivalent of more than one full NPA code. SMS/800, Inc. (SMS/800) works with members of the toll-free industry to announce the opening of a new NPA code at least 30 months in advance of the exhaust of the existing pool of TFNs, pursuant to the ATIS industry guidelines. Accordingly, SMS/800 has an ongoing forecast effort to assess when, or even if, the available TFN number pool will exhaust.

Prior to the first quarter of 2008, the method used to assess when TFN capacity would exhaust was to divide the quantity of spare numbers by the most recent six-week rolling average of weekly TFN growth[4]. This approach produced weekly results that were highly volatile. In the first few months of 2008, this method produced exhaust dates which differed by more than *two centuries*, varying from October 2009 (Weekly Number Administration report of February 29, 2008) to December 2217 (Weekly Number Administration report of January 12, 2008). Clearly, this method produced results that fluctuated, sometimes substantially, each time the forecast was performed. This was not conducive to making sound business decisions. In particular, these fluctuations made it difficult to prepare for the opening of the next toll-free NPA, for which a substantial lead time is required. Hence, to plan adequately for this eventuality, a more stable long-run forecasting approach was needed. The objective of the current forecast method is to produce a TFN forecast that:

- does not fluctuate substantially with relatively minor changes in recent values of TFN usage;
- is based on long-term historical patterns in TFN usage rather than short-term perturbations;
- is generated by a defensible, empirical methodology; and,
- quantifies the uncertainty inherent to any forecast by including a range of results and an evaluation of risk of exhaust over time.

The TFN forecast performed in January 2015 is consistent with, and builds upon, the work performed in previous TFN forecasts.

2 Forecasting Approach and Basic Methodology

As the steward of the TFN pool, SMS/800 has a responsibility to ensure that its customers, telecommunications carriers and the toll-free subscriber community have timely access to sufficient quantities of toll-free numbers (TFNs). One of SMS/800's most important responsibilities is to monitor the use of TFNs and alert the telecommunications industry of any impending exhaust of the TFN pool. Current industry guidelines suggest that SMS/800 notify the OBF SNAC when exhaust of the TFN pool is expected to occur within 30 months. The specified lead time for this announcement has an important implication for the design of the forecasting methodology as it ties the forecast outcomes directly to SMS/800's critical business decision. The lead time of 30 months directs the methodology's forecast horizon through which forecasts must be sufficiently reliable to inform and aid SMS/800's business decisions.

The forecasting approach could rely on a strictly new analysis and assume a clean slate each time a TFN forecast is undertaken. This clean slate approach would examine a wide range of statistical and econometric forecasting techniques, require significantly more calendar and staff time and be much more expensive. In April 2008,

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[3] Although there are 10 million 10-digit TFNs within each NPA, NANPA has closed the following NXX codes in each NPA: 0XX, 1XX, and 911. Further, the 555 NXX is closed for all NPAs except 800, and the 800 NPA has 11 additional NXXs closed. In addition, some TFNs within each NPA are used for testing purposes and others remain unavailable for reservation for various reasons.

[4] This approach is similar to that described in the "Toll Free Resource Exhaust Relief Planning Guidelines" (ATIS-0300057), published July 1998, which are examined in Appendix A.

SMS/800 examined alternative forecasting methodologies including econometric models. That effort established that time series analyses were superior to alternative methods. Even today, given the forecast purpose, approaches such as leading indicators and econometric models are unlikely to be superior to time series forecasting. Tentative exploration has revealed no indicators with lead times approaching 30 months. TFN forecasts using econometric models would require reliable forecasts of causal variables (possibly macroeconomic) as much as 30 months in the future. This requirement would be difficult to satisfy. Thus, SMS/800 has adopted a purely statistical, time-series forecasting approach. This approach relies on past values of TFN use and captures changes in the rate of change over time. It generates TFN forecasts as well as measures of the uncertainty surrounding these forecasts at particular decision dates in the future. Rather than relying on a single statistical model, this approach considers multiple statistical models from which the best models are selected.

2.1 Statistical Time Series Models

SMS/800's approach "follows the data." The behavior of the TFNs has not changed radically since the last TFN forecast in July 2014 and, thus, the approach does not change radically, incorporating all that SMS/800 has learned about this data set over the last several years. As with recent work in TFN forecasting, success in using ARIMA models leads to consideration of these models again for forecasting TFNs.[5] In addition, past analyses have also explored the application of various types of time trend regressions and Autoregressive Conditional Heteroskedasticity (ARCH/GARCH)[6] modeling techniques. The latter may be useful to address fluctuations in the variance in the error terms that tend to arise with the use of longer samples of historical data. SMS/800 again considered both time-trend regressions and ARCH/GARCH techniques as well as the use of full and truncated samples of historical data.

It should be noted that statistical time-series methods, while generally sound and defensible, essentially assume that past behavior is a window into the future. They implicitly assume that TFN usage will exhibit essentially the same behavior in the future as it has over the historical period used to estimate the model. If historical TFN usage has increased rapidly, then the forecast should show continued rapid growth. Alternatively, if historical TFN growth has been gradual, then forecasted TFN growth should generally exhibit the same behavior. These statistical techniques are designed to assess the volatility and implicit weighting of past growth patterns in ways that non-statistical techniques cannot. Moreover, these statistical techniques are predicated on assessments of their demonstrated forecast accuracy and can assess the risk associated with announcing or delaying future code openings at specific future dates. Non-statistical techniques, e.g., using a "ruler" to draw linear trend lines, offer no such assessments of forecast performance or appraisals of the risk incurred by timely business actions or the consequences of inaction.

2.2 Hold-Out Tests

The weekly, monthly and quarterly data sets used in this forecasting effort were each bifurcated into an estimation period and a hold-out period. The latter is used for model selection by testing and comparing the forecast accuracy of models calibrated using the same (or even different) estimation period(s). This process of testing and comparing the out-of-sample forecast accuracy of alternative models helps to ensure that the models ultimately used to forecast TFN are robust—that is, the models will represent the growth of TFNs appropriately as the future growth in TFNs unfolds. Use of a 30-month hold-out period is preferable since this corresponds to the SMS/800 business decision, i.e., the announcement lead time for the toll-free industry to implement a new toll-free code.

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[5] A time series forecasting technique such as ARIMA relies on observations of data at regular time intervals. For the sake of discussion, the illustration in this footnote uses "month" as the time interval of observation. An ARIMA model, summarized by ARIMA (p,d,q), can be characterized by three categories of parameters: p, the longest number of months by which past data directly influence current data, also referred to as the autoregressive (AR) term; d, the number of times the series (i.e. TFN) is differenced to recognize the degree of increase or decrease over time; and q, the longest number of months by which lagged forecast errors improve the prediction of current data. The lagged forecast error q term is also referred to as a "moving average" (MA) term; this term is akin to creating an exponentially weighted average of past data (of TFN or its degree of increase or decrease in this instance), with the most recent data given the highest weight and the weights assigned to older data exhibiting exponential decay.

[6] GARCH and ARCH terms, described later.

As past TFN analyses reflect, however, limited sample sizes and the occurrence of various external events often have inhibited the use of 30-month hold-out periods.[7] Ideally, hold-out samples should contain observations of TFN usage that are undisturbed by external shocks or events such as code openings, TFN rationing, etc. Given current rates of TFN usage and guidelines requiring 30-month notice of a code opening prior to exhaust, however, periods of undisturbed TFN usage exceeding 30 months may be unlikely or rare. Even 24 or 30-month periods of undisturbed TFN usage behavior may be rare. Thus, the length of hold-out samples used to test models must be specific to the circumstances at the time of each analysis.

For this forecast, as was the case in the July 2014 forecast, the opening of code 844 in December 2013 and a period of unusual growth in March 2013 may obfuscate the interpretation of long hold-out samples for model selection and testing. As in the July 2014 study, anticipating such problems, we examined models using the following four alternative sets of hold-out samples: 12 months, 18 months, 24 months and 30 months. Each of these divisions of the available data was further refined by considering separately models using weekly, monthly and quarterly end-of period data. Estimation samples were examined using two different starting points for the historical data:

- A full historical sample from August 1997 to December 27, 2014; and,
- A truncated historical sample from October 1, 2003 to December 27, 2014.

Thus, the analysis spans 24 different designs for analyzing and testing models with the available data: (4 hold-out definitions) X (3 periodicities) X (2 historical sample lengths).

2.3 Model Selection

Various statistical model specifications were estimated with data from the estimation periods.[8] The forecasts from these models were then compared to the actual TFN values for the corresponding common hold-out periods. Better performing models were re-estimated using the full sample of data (through December 27, 2014).

The candidate models were assessed on the basis of the following characteristics:

- statistical significance of the modeled terms;
- whether the resulting in-sample residuals appeared to be random (i.e. exhibited "white noise");
- the principle of "parsimony" (i.e. the fewest terms required to fit the data and produce white noise);
- the magnitude and nature of forecast errors in the hold-out period as measured by Mean Percent Error (MPE), Mean Absolute Percent Error (MAPE) and Theil's measures of forecast bias and variance;
- the size of the confidence interval around the forecast estimate;
- robustness (i.e. whether the terms and/or their coefficients changed significantly when the models were re-estimated with the full data set); and,
- whether the forecasts made sense based upon our knowledge of TFNs.

[7] Because insufficient time had passed since the 2010 code opening, the fall 2011 forecasting analysis relied on a hold-out period of only 18 months rather than 24 months as in spring 2010. In spring 2012, sufficient time had elapsed to return to a 24-month hold-out sample but not the preferred 30-month. In October 2012 sufficient time had passed since the 855 code opening and the historical sample was then large enough that a 30-month hold-out sample from April 2010 through September 2012 was used.

[8] The specific data for the estimation period are determined by the length of the hold-out period. For example, with a 30-month hold-out period and monthly data, the hold-out period is July 2012 to December 2014, while the estimation period using the full historical sample is August 1997 to June 2012.

2.4 Risk Assessment

SMS/800 has expanded the scope of its forecast analysis to assess more explicitly the risk of exhaust or, equivalently, the odds that spares remain in the pool. These values are more germane to the business decision of starting the process to open a new toll-free NPA. This risk assessment utilizes information about the variance underlying the model forecasts, information similar to that used in creating a confidence interval around an estimate. This is described in more detail below.

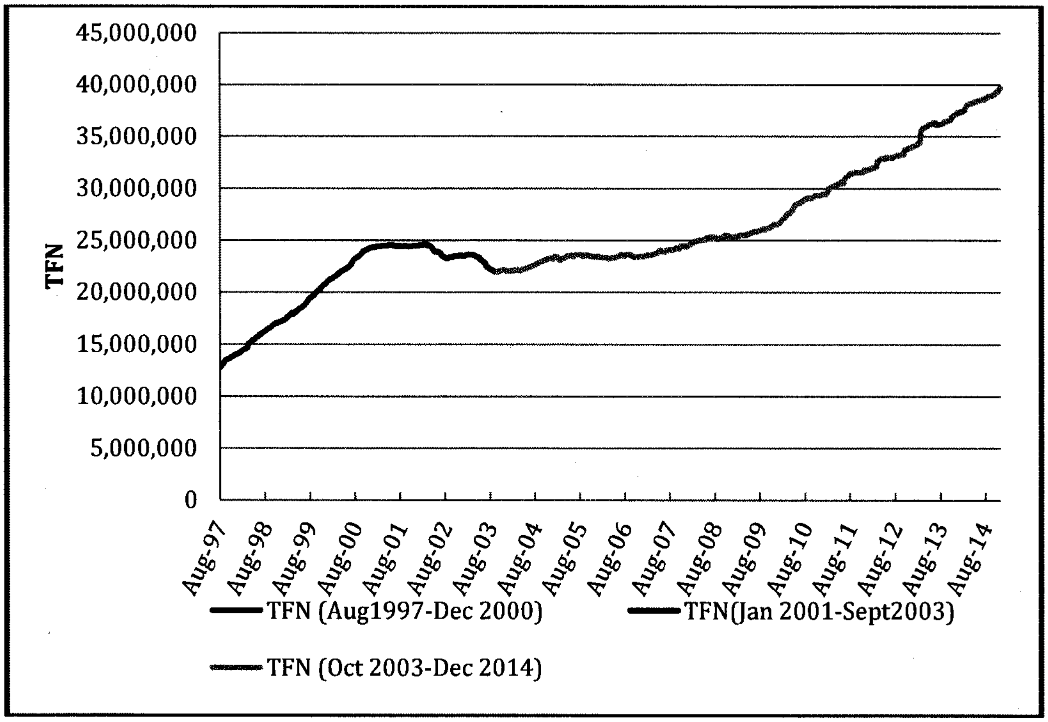
3 The Data Set and Sample Period

Weekly historical data for TFNs in Use are available starting August 23, 1997 and continuing through December 27, 2014 (906 weeks in total).[9] A monthly end-of-period TFN series was created by taking the last weekly value within each month starting in August 1997 (209 months). A quarterly end-of-period TFN series (70 quarters) was created by taking the last weekly value within the quarter beginning with the third quarter of 1997.

As shown in the graph below, the historical TFN sample exhibits 3 distinct periods:

- **1997 to 2000**: marked in blue by a very rapid rise in TFN (average monthly growth of 1.6%);
- **2001 to 2003**: marked in red by an abrupt cessation of the growth in TFN, followed by a decline (average monthly growth of -0.25%);
- **2004 to 2014**: marked in green by a return to rising TFN, initially growing more slowly than the late 1990's but gradually accelerating (at least through 2010).

Figure 1: TFN Growth Varies over the Historical Sample



[9] Several "gaps" in the weekly series prior to 2002 were filled in using a simple interpolation method. All data provided were assumed to be accurate. No cleansing of raw data was done to correct potential typos or other errors.

Given the accelerating growth experienced after 2004, a truncated sample beginning in October 2003 is also employed in this analysis.

In the past, there had been some concern about sufficiency of sample size when using quarterly data. A statistical rule of thumb is to employ samples with 40 or more observations for ARIMA modeling. Even if a truncated sample beginning October 2003 is used, sufficient data are available to estimate weekly, monthly and quarterly models; though in the latter case, the number of data available is *minimally* sufficient. Specifically, a 10-quarter (i.e., 30-month) hold-out sample drawn from a truncated sample beginning in October 2003 leaves an estimation sample of only 35 quarters (or 60 quarters using the full historical sample). Even taking into account the effects of differencing and lagged terms, this sample size of 35 observations is minimally sufficient to attempt ARIMA analyses. The table below clearly shows, though, that much more data are available when using the full historical sample and/or shorter hold-out samples.

Table 1: Full and Truncated Sample Sizes

	Sample Size	
	Oct 2013 – Dec 2014	Aug 1997 – Dec 2014
Weekly	587	906
Monthly	135	209
Quarterly	45	70

The use of the full historical sample (shown in the graph above), while providing more data, means that first difference models are estimated across a data set in which the variation in the data changes significantly across time periods; this has the potential to produce *heteroskedasticity* in the estimated residuals of the models. To address this issue, (i.e. to improve the statistical efficiency of the long-run forecasts) ARCH/GARCH terms[10] are often employed in the modeling process.[11] Previous TFN forecasts have indicated that the introduction of ARCH/GARCH terms may improve the modeling of TFN time series and the analysis of risk for business decision-making.

4 Context Relative to July 2014 Forecast

The previous TFN analysis in July 2014 forecasted exhaust in third quarter, 2018. The data problems cited in section 2.2 above regarding hold-out samples were even more limiting in July 2014 and led to using only 6-month and 12-month hold-out samples for model selection. In fact, model selection was based primarily, but not exclusively, on the 6-month hold-out tests. No models performed well in longer hold-out samples. As discussed earlier, reliance on hold-out tests of 12 months or less is clearly not ideal when formulating models for a forecast horizon exceeding 30 months.

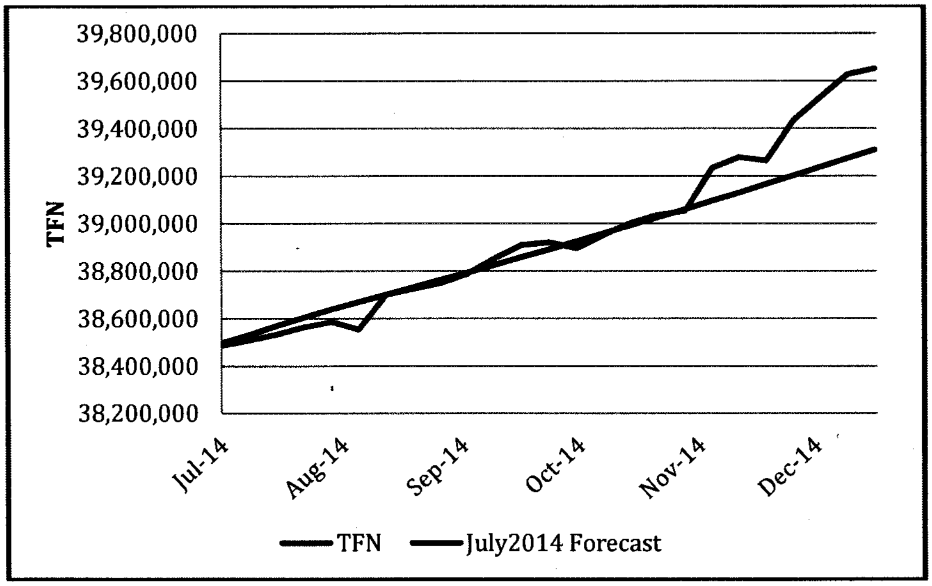
The graph below compares the July 2014 forecast with TFN data from the last six months of 2014. By the end of 2014, forecasted TFN was 0.86% less than TFN. If this pattern should continue, exhaust might occur earlier than the forecasted third quarter of 2018. An error of this size should not cause alarm, nor should the possibility of earlier exhaust. After all, the July 2014 forecast report warned that the odds of spares remaining in the pool would fall to only 2:1 as early as third quarter, 2017. That is, the July 2014 report stated that there was one chance out of three that exhaust might occur as early as third quarter, 2017. Moreover, the July 2014 forecast

[10] An autoregressive conditional heteroskedasticity (ARCH) modeling term considers the variance of the current error term to be a function of the variances of the previous time periods' error terms. It is employed commonly in modeling financial time series that exhibit time-varying volatility clustering. If an autoregressive moving average model is assumed for the error variance, the model is a generalized autoregressive conditional heteroskedasticity (GARCH). See, e.g., http://en.wikipedia.org/wiki/Autoregressive_conditional_heteroskedasticity.

[11] GARCH addresses the residual variance in TFN still unexplained after the ARIMA modeling. For example, the weighted lagged squared residual represents "news" about the evolving variance.

analysis has provided insights that have aided the current effort, especially in terms of analytical design of estimation and hold-out samples, model specification, and forecast interpretation.

Figure 2: July 2014 Forecast May Underpredict



5 Model Estimation and Selection

Over one hundred ARIMA and time trend models with varying data samples and specifications were estimated, encompassing 24 different designs based on sample size, hold-out length and data frequency. As part of this process, first and second-differenced TFN series, some with log transformations and some without, were examined using weekly, monthly and quarterly end-of-period data. ARCH and GARCH terms were also examined to assess their ability to improve hold-out sample performance.

Hold-out tests employed samples of 30, 24, 18 and 12 months. Viable models emerged from each of the four hold-out tests, but no models dominated across all four hold-out samples. The table below displays the best candidate models resulting from the estimation process and hold-out evaluations.

Table 2: Best Candidate Models

Model	Periodicity	Sample	MAPE in Hold-Out Test			
			30 mo	*24 mo*	*18 mo*	*12 mo*
1. ARIMA214	QTR	FULL	7.19	5.53	0.48	0.46
2. DLTIMER	QTR	TRUNC	2.14	1.53	4.37	1.66
3. DMA12	MNTH	TRUNC	4.47	4.59	0.23	0.33
4. LDTIMER	MNTH	TRUNC	1.93	1.24	4.12	1.56
5. LDTIME_ARGAR2	WEEKLY	TRUNC	1	1.22	3.76	1.13
6. ARIMA223	QTR	TRUNC	1.21	1.35	3.41	1.69

As shown in column 3 above, one model was estimated using data beginning in 1997 (FULL) representing the full historical sample, and five other models were estimated using the truncated sample that consists of data beginning in October 2003 (TRUNC):

- One model employs weekly data; two, monthly; and three, quarterly;
- Because TFN data have a positive trend (i.e., TFN data are clearly non-stationary), differencing is necessary. Five of the models use first-differenced data and ARIMA223 uses second-differenced data (which allows for accelerating incremental growth);
- Three models (2, 4 and 5) embody compounding growth (percentage growth rates), while models 1, 3 and 6 embody incremental growth; and,
- Model 5 adds ARCH/GARCH terms.

Note the MAPEs for the four different hold-out samples. No model is best across all hold-out samples:

- LDTIME_ARGAR2 (model 5) does moderately well across all hold-outs, but is best only in the long hold-out samples. But, this model's ARCH/GARCH coefficients are not statistically significant in all samples;
- Models 2, 4 and 6 perform relatively well in the long hold-out samples, but poorly in the short samples; and,
- Models 1 and 3 perform well in the short samples, but poorly in the long samples.

In addition to MAPE, bias was also reviewed. Examination of bias reinforced the model summary above based on MAPE; but, LDTIME_ARGAR2 (model 5) was more biased than some other models, especially in the shorter hold-out samples.

5.1 Meta Models

In prior forecasting efforts, SMS/800 has employed combinations of models (i.e., "meta" models) when there was no clear "winner" among candidate models. If different models have different strengths, selectively combining the models can draw on the strengths of each candidate model to produce forecasts superior to those of the individual models.

In the current analysis, because no single model dominated across all hold-out samples, meta models were developed for each hold-out sample: 30, 24, 18 and 12 months. Step-wise regression was used to search for the best linear combination within each hold-out sample. Similar to the individual model analyses, candidate meta models were then evaluated based on MAPE and bias. Each of the meta models in the table below had the lowest MAPE and was unbiased in its respective hold-out sample. The table identifies the candidate models combined to form each meta model and the weighting of each component model.

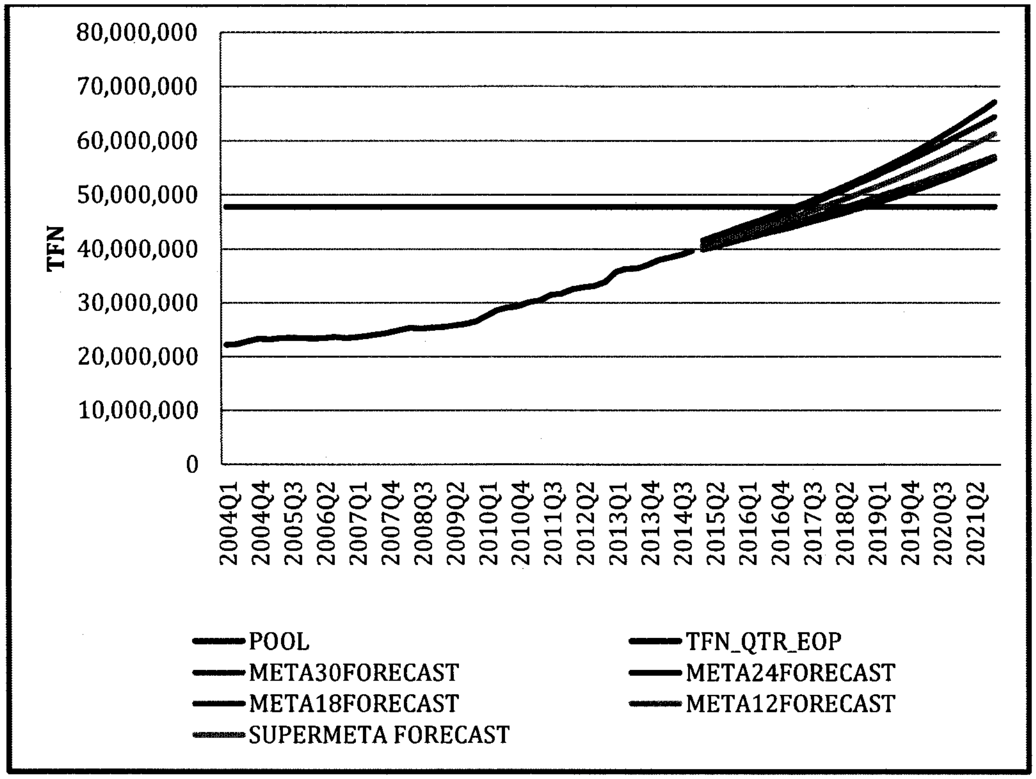
Table 3: Four Meta Models

Model	***Component Models***	***Weight***	***MAPE***
META30	ARIMA214 ARIMA223	0.18 0.83	0.9
META24	DLTIMER DMA12	0.41 0.62	0.327
META18	ARIMA214 LDTIME_ARGAR2	0.70 0.29	0.178
META12	ARIMA223 DMA12	0.39 0.60	0.057

6 Forecasts

Forecasts for the meta models in the table above were calculated from their component model forecasts. Because each meta model was calibrated to address the data characteristics of its particular hold-out sample, no meta model dominates across all hold-out samples. Not surprisingly, the meta models for the 30 and 24 month hold-out samples capture the accelerating growth in TFNs through 2013. These two meta models forecast relatively early exhaust in 2017. The meta models for the 18 and 12 month hold-out samples are tuned to the more subdued growth from the second half of 2013 through the present. These meta models forecast exhaust in 2018. As the statistical data indicate no single meta model is superior, these four forecasts were then averaged to obtain a SUPER META forecast.

Figure 3: Forecast Alternatives



Current TFNs available for use total 47, 770,094. As seen in the graph above and table below, the four underlying meta models produce a range of exhaust dates from quarter 2, 2017 (META24), through quarter 4, 2018 (META18). The SUPER META, however, predicts exhaust in quarter 1, 2018. (In the table below, forecast demand in the anticipated month of exhaust is shown in bold.)

Table 4: TFN Demand and Exhaust Date Forecasts

DATE	META30	META24	META18	META12	SUPER META
2015Q1	40,716,915	41,559,358	39,774,669	39,812,084	40,465,757
2015Q2	41,304,157	42,232,410	40,305,026	40,336,301	41,044,473
2015Q3	42,150,653	42,909,548	40,852,934	40,971,282	41,721,104
2015Q4	42,913,156	43,666,844	41,425,201	41,626,347	42,407,887
2016Q1	43,549,501	44,347,561	41,944,137	42,138,940	42,995,035
2016Q2	44,378,273	45,046,180	42,440,160	42,746,922	43,652,884
2016Q3	45,172,899	45,763,502	42,929,519	43,341,005	44,301,731
2016Q4	45,856,209	46,500,369	43,446,746	43,883,617	44,921,735
2017Q1	46,688,891	47,257,666	43,919,615	44,497,785	45,590,989
2017Q2	47,530,637	**48,036,329**	44,428,167	45,116,732	46,277,966
2017Q3	**48,274,186**	48,837,339	44,977,548	45,689,476	46,944,637
2017Q4	49,125,755	49,661,734	45,512,223	46,313,675	47,653,347
2018Q1	50,011,529	50,510,606	46,061,105	46,954,304	**48,384,386**
2018Q2	50,815,729	51,385,104	46,625,119	47,556,465	49,095,604
2018Q3	51,694,125	52,286,444	47,205,141	**48,193,973**	49,844,921
2018Q4	52,620,212	53,215,904	**47,802,050**	48,854,261	50,623,107

6.1 Risk Assessment

Although forecasting an exhaust date is helpful in determining when the industry should announce a new code, it does not adequately convey the degree of risk and uncertainty as to when exhaust may occur. Meteorologists, for example, present rain forecasts as "the chance of rain" on a particular date. Their audience weighs the probability of rain to decide whether to carry an umbrella, drive rather than bike to work, or cancel a tee time. Similarly, each future date in the TFN forecast has an associated probability of whether exhaust will occur at that time.

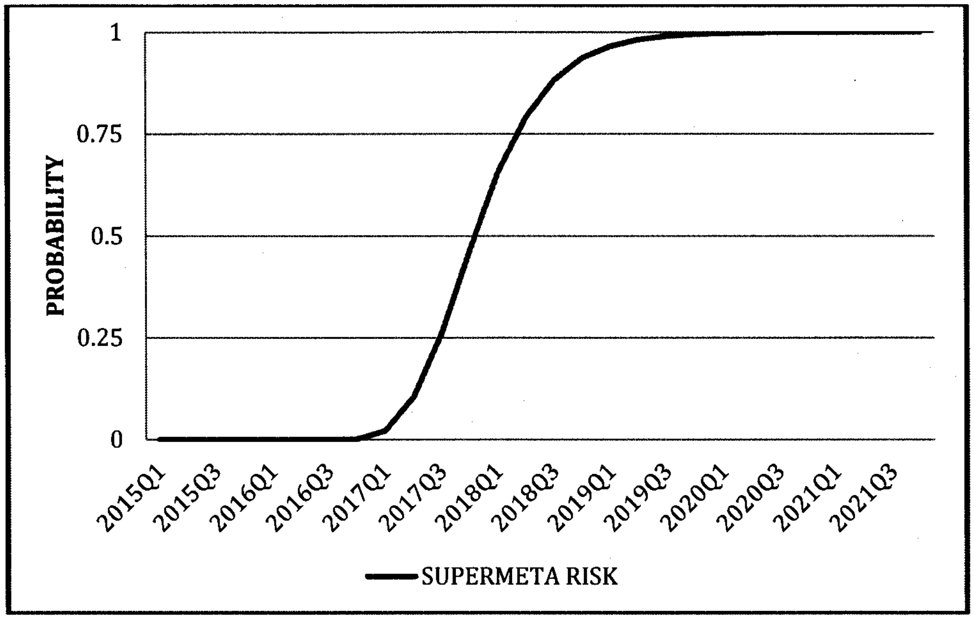
In a forecast of future TFN growth, forecast risk occurs because historical data demonstrate that the growth in TFNs is variable. At times, usage can accelerate quickly, as occurred during the late 2009 to early 2010 period and during March 2013; at other times usage can decelerate or even decline as occurred in 2000-2003. While the TFN forecast provides the most likely exhaust date, the forecast risk warns that history has demonstrated that earlier exhaust is clearly possible.

The exhaust date forecast presented above is the most likely date that exhaust will occur—that is, the date at which there are equal chances of spares remaining as spares exhausting. As noted above, SMS/800 augments the point forecasts with an assessment of the risk of exhausting the TFN number pool sooner than the date of the point forecast. The estimated risk values are germane to the business decision of when to start the process of opening a new toll-free code.

An analogy from the retail sector emphasizes the importance of considering fluctuations in future demand. Compare management of the pool of spare TFNs to a retail manager's decisions regarding store inventory. The retail manager wishes to avoid running out of stock, as this can frustrate customers. Nor does the manager want to hold excessive inventory or restock too early as either can be costly. The manager must also consider how far in advance to place an order before the new stock is delivered. The longer the order time, the greater the difficulty and possible error of forecasting stock remaining at time of restocking. Furthermore, the manager is concerned that if some customers should lose confidence that the store's inventories will be adequate, such customers could cause a run on the store, exhaust the stock and frustrate other customers. Such speculative acquisition might spread among customers, increase the volatility of sales and make future inventory management even more difficult. For all of these reasons, the manager approaches inventory decisions cautiously. The manager optimizes inventory and restocking by balancing the expected variation in future demand for his product (the risk of running out of stock) against the cost of holding inventory and restocking. Similarly SMS/800 and the industry must balance the expected future variation in TFN demand against the timing and costs of opening a new code. Thus, whether addressing the stock of retail product on hand or the pool of spare TFNs, managing inventory well requires assessment of the volatility of future demand as well as the risk of exhausting the stock early.

As applied to the management of toll-free numbers, risk of exhaust on a particular date is defined here as the probability that TFN demand on that date exceeds the pool of TFNs available under existing codes. For example, risk of 25% on a specific date suggests that there is a one in four chance that TFNs will exhaust by that date, or 3:1 odds against exhaust. Risk of 50% on a specific date suggests there are even odds (i.e. 1:1) that any spare TFNs remain available. This is the most probable date of exhaust. After that date, the odds are higher than 1:1 that TFN demand will exceed the stock of available numbers.

Figure 4: Risk of Exhaust



The most likely date of exhaust corresponds to a risk of 50%--i.e., on that date there are equal chances (or even odds) that TFNs in use will exceed or fall short of current TFNs available. Risk of exhaust begins to accelerate much earlier, however. For example, the SUPER META forecast indicates that the risk of exhaust exceeds 25% during third quarter of 2017. Or stated as odds, by the third quarter of 2017, the odds of spares remaining in the pool versus no spares remaining (exhaust) are less than 3:1. The risk of exhaust escalates rapidly during the second half of 2017.[12]

More specifically, the following table shows forecasted spares as a percentage of the pool, the corresponding percentage of the TFN pool that is in use and the probability that spares remain in the pool.

[12] As the forecast horizon shortens and the number of observations increases, the precision of the forecast should improve. Thus, in the current forecast the odds of spares remaining in third quarter 2017 are 3:1 versus 2:1 in the July 2014 forecast, even though the current analysis predicts an earlier exhaust date.

Table 5: Exhaust Benchmarks and Associated Risk

Spare % of TFN Pool	% of TFN Pool in Use	Date	Probability of Exhaust	Probability that Spares Remain
15%	85%	2015Q2	Less than 1%	Over 99%
10%	90%	2016Q1	Less than 1%	Over 99%
5%	95%	2017Q1	Less than 3%	Over 97%
3.1%	96.9%	2017Q2	10%	90%
1.7%	98.3%	2017Q3	26%	74%
0.2%	99.8%	2017Q4	47%	53%
0%	100%	2018Q1	66%	34%

7 Interpretation and Conclusions

The forecasts of the four meta models reflect a possible change in the growth path of the TFN usage. Prior to the spike in TFN usage in March 2013 and the opening of code 844 in December 2013, the rate of growth of TFNs was faster and possibly accelerating. Since the opening of 844, the rate of growth of TFNs has been more moderate than its long-term historical pattern from 2003 to 2013.

The meta models corresponding to the longer hold-out samples of 24 and 30 months reflect the faster and accelerating growth prior to the opening of code 844. The meta models corresponding to the shorter hold-out samples of 18 and 12 months reflect the slower more linear growth that has followed the opening of code 844. The forecast hinges on which of these patterns will prevail over the next three or more years.

Without additional information regarding the cause of the recent change in TFN behavior, statistical time series methods alone cannot reconcile the two scenarios. One set of meta forecasts suggests that TFN growth will eventually return to its long-term pattern, one marked by accelerating growth, and exhaust the current pool sometime in early to mid 2017. The other suggests that TFN growth will remain more moderate than its long-term pattern and exhaust the current pool later in 2018.

The SUPER META forecast does not resolve this underlying statistical quandary, but merely straddles the two positions to create a "most likely" scenario that balances the possibilities with equal weights. Thus, the most likely exhaust date is sometime between early-2017 and late-2018; the SUPER META suggests early 2018.

In summary, the recent rate of growth of TFNs following the opening of code 844 has been more moderate than its historical pattern from 2004-2013. The July 2014 TFN forecasts projected the continuation of this slower rate of growth, but these forecasts have fallen slightly behind current TFN usage. The current TFN forecast predicts that exhaust will occur sometime between early-2017 and late-2018, but most likely in early 2018. Furthermore, the risk of earlier exhaust rises dramatically during the second half of 2017, and the number of spares remaining in the pool is expected to fall below 5% by the end of first quarter 2017. For planning purposes, decision makers should be very wary that the long-term pattern of accelerating growth might again prevail. Resumption of faster TFN growth would lead to earlier exhaust—probably in 2017.

8 Recommendations

1. Open code 833 at the end of first quarter, 2017.

   Rationale: SNAC recently recommended opening code 833 on June 30. 2017. While this is prior to the currently forecasted TFN exhaust in first quarter of 2018, only 3.1% of the pool is forecast to remain by that date. Furthermore, probabilistically, the risk of exhaust starts to escalate very rapidly during the second half of 2017. Conservative practice suggests an earlier opening to guard against exhaust. If by April, 2015 SMS/800 were to recommend a code opening date of April 1, 2017, the industry would have two years to prepare for the new code and the announcement would be more than 30 months prior to the forecast exhaust of first quarter, 2018.

2. Monitor TFN growth carefully to see if TFN growth accelerates toward its long-term historical path.

   Rationale: While recent growth in TFNs has been more moderate, long-term patterns of TFN change reflect faster, accelerating growth. Resumption of such accelerating growth would exhaust the existing pool of TFNs more quickly, possibly even earlier than spring, 2017.

3. Develop and be ready to implement contingency plans to address the possibility of early exhaust.

   Rationale: Even if code 833 were opened April 1, 2017, resumption of accelerating growth could exhaust the existing pool of TFNs even earlier. It is prudent to prepare a contingency plan to address this possibility.

8.1 Caution

The statistical techniques used to develop these projections rely on historical data and, thus, cannot predict turning points or dramatic changes in TFN growth that are not implicit in the historical data. <u>Recent patterns of TFN growth from 2013 to present raise some question about whether the historical pattern may be changing.</u> Thus, the forecasting exercise that SMS/800 has performed simply describes the most likely date that toll-free number capacity will be reached *if the data patterns of August 1997 through December 2014 should continue into the future in the manner discussed above in this report.* Because the pattern may be changing, it is very important to monitor developing trends closely and track them against the forecasts as new TFN data become available.

Appendix A – ATIS Approach to Determining an Exhaust Date for the TFN Pool

SMS/800 believes that statistical analyses, such as those described within the body of this report, are the most appropriate methods for projecting the exhaust of the TFN pool. Further, SMS/800 believes that statistical methods have the ability to assess risk surrounding the business decisions related to the exhaustion of the TFN pool (e.g., the risk that the TFN pool will exhaust sooner than the point estimate). However, ATIS has established a method for identifying the date at which the industry should be notified of an impending code opening. This approach is described in the "Toll Free Resource Exhaust Relief Planning Guidelines" (ATIS-0300057), published in July 1998.

Within that planning guide, exhaust of the TFN pool is determined by inputs for "average demand" and "accelerated demand" to be provided by SMS/800. The prescribed steps to determine the predicted number of months remaining until exhaust of the TFN pool are represented by the following formula:

$$\frac{\text{Spares} - (\text{Accelerated Demand} * \text{Quantity of Months of Accelerated Demand})}{\text{Average Demand}} + \text{Quantity of Months of Accelerated Demand}$$

The approach is appealing in that it is a straightforward and simple calculation. However, as the inputs for "average demand" and "accelerated demand" are not well defined, the approach is prone to be arbitrary and can lead to highly volatile results based on different input choices. Further, the sample size to be used for the analysis is also undefined, creating another layer of arbitrariness that effects the results. However, it remains SMS/800's understanding that the ATIS approach is the official method for determining when the toll-free industry should be notified of a code opening and, thus, a version of the method was examined.

SMS/800's variation on this approach relies upon more narrowly defined inputs, including:

- "Average demand" is defined as the average of all data points within the selected sample which fall within a range of the overall sample average plus and minus the sample standard deviation; and,
- "Accelerated demand" is defined as the average of all data points within the selected sample which are greater than the overall sample average plus the sample standard deviation.

For the input related to the number of periods at accelerated demand, rather than simply inputting an arbitrary value, SMS/800's approach calculates how many times historical demand has exceeded the accelerated demand within the sample period. This percentage is then used within the revised formula below:

$$\frac{\text{Spares}}{(\text{Average Demand} * (1 - \text{percent of periods above Accelerated Demand}/100) + (\text{Accelerated Demand} * \text{percent of periods above Accelerated Demand}/100))}$$

Furthermore, SMS/800's approach considers both monthly and quarterly data as well as many different sample sizes for monthly and quarterly data. Not surprisingly, the period over which the data are considered has a significant impact on the results. For the purposes of this exercise, SMS/800 examined all TFN data available and based the ATIS approach on this data set. The following two tables are representative of the results based on the analyses performed on the monthly and quarterly data series.

Table A: Range of Results - Months

ATIS Exhaust Approach - Months						
# of Months in Sample	**12**	**18**	**24**	**132**	**168**	**208**
Spares	8,119,261	8,119,261	8,119,261	8,119,261	8,119,261	8,119,261
Average Demand	154,084	153,719	183,490	110,953	88,204	120,873
Accel Demand	480,579	455,305	1,057,955	611,458	587,055	508,717
%-age of periods at accel demand	17%	17%	8%	8%	7%	11%
Quarters to Exhaust	38.9	39.8	31.7	53.2	65.6	50.2
Exhaust Date	Mar-18	Apr-18	Aug-17	Jun-19	Jun-20	Mar-19

Table B: Range of Results – Quarters

ATIS Exhaust Approach - Quarters						
# of Quarters in Sample	**4**	**6**	**20**	**44**	**56**	68
Spares	8,119,261	8,119,261	8,119,261	8,119,261	8,119,261	8,119,261
Average Demand	562,438	648,564	676,111	338,234	220,090	363,230
Accel Demand	814,684	1	1,456,463	1,047,367	955,568	1,136,293
%-age of periods at accel demand	25%	0%	10%	16%	18%	13%
Quarters to Exhaust	13.0	12.5	10.8	18.0	23.1	17.4
Exhaust Date	1Q2018	1Q2018	3Q2017	3Q2019	4Q2020	2Q2019

As seen in figures A and B above, the ATIS approach indicates exhaust between:

- August 2017 and June 2020 with monthly data; and,
- quarter 3, 2017 and quarter 4, 2020 when relying on the quarterly data.